Achieving "Just Press Print" for Metal Additive Manufacturing

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Part qualification for critical applications can be costly and take a long time (up to a decade)—attributes that offset the speed, versatility, and adaptability of additive manufacturing. Fifty-six percent of manufacturers surveyed indicated that uncertain quality of the final product was a barrier to adoption of additive manufacturing. The challenge is to replace the experience-based approach presently used to produce parts with a science-based, automated approach that can be implemented on the factory floor.

Qualification has three major components: engineering qualification, production qualification, and materials qualification. Because with additive manufacturing we are creating the material at the same time as we create the part, materials qualification becomes an issue. Addressing metal additive manufacturing part qualification is a multidisciplinary problem requiring experts in mechanical engineering, materials science, computer science, data science, and photon science. At Lawrence Livermore National Laboratory, we are pursuing a comprehensive experimental and modeling and simulation strategy that includes all of these disciplines with the goal of accelerating part qualification. We employ a multiscale modeling framework that includes models of powder spreading dynamics, powder melting and solidification, microstructure development during solidification, and residual stress and distortion at the part scale. The experimentally validated models describe what can be expected from a build carried out with specific input parameters, but such predictions alone do not provide the accelerated qualification that is required.

Today, we use extensive, iterative experimentation to optimize input parameters for the process such as the laser power, speed, and beam size. However, because the thermal boundary conditions change as a function of the part geometry, the parameters required to achieve desired part quality will also be a function of geometry. In current powder bed fusion systems, geometry-specific parameters can be entered only for simple shapes such as overhangs or contours. During the build, data is collected from in situ process sensors. In situ sensors and feedback schemes aid with process control. But, feedback works best when the input parameters are close to optimal for the given geometry. Achieving the needed control throughout a part build requires voxel-by-voxel control of the input parameters. The vision of achieving a precise, optimized 3D map of input parameters is referred to as *a priori* or *intelligent feed forward* control.

Modeling and simulation, combined with high-performance computing optimization, have the potential to move us to the next stage in controlling the process. In this methodology, the simulation will be used to *teach* the additive manufacturing machine how to build the part on a voxel-by-voxel basis and at the same time predict the output of the process sensors. Because we cannot expect the simulations to be perfect, feedback control will be used to correct the simulation-based build. After the build is complete, the sensor data will be compared with the simulation's prediction. If the prediction and the experiment agree within some specified uncertainty, we believe that it will be possible to establish confidence with product engineers that the material is of the required quality to fulfill mission requirements.

As we learn more about the detailed physics of laser-powder interactions, melt-pool dynamics, microstructure development, and thermal stresses during cooling, the capabilities of the detailed simulation models will improve. However, in addition to being based on the knowledge gained from detailed high-performance computer simulations, a true *intelligent feed forward* predictive model will need to be based on fast-running, reduced-order simulations that can be run for every new part or configuration to be manufactured (at the local machine level). Development of sufficiently accurate, rapid, reduced-order predictive models will be the key to wide application of the *intelligent feed forward* concept. That is a new challenge that will have to be met.

The *intelligent feed-forward* approach, when successfully implemented, will ensure "right every time" production or early automated rejection, thus buying down risk. The approach is meant to be agnostic to feedstock, machine, and geometry. In ten years' time, we believe that every metal additive manufacturing machine will have *model-based intelligent feed forward* capability, which will enable engineers and technicians to "just press print" for metal additive manufacturing.

This work performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344